# On the choice of the initialisation method for seasonal-to-decadal predictions

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## 1. Introduction

- Full Field (FFI) and Anomaly Initialization (AI) are two approaches used for the initialization of seasonal-to-decadal (s2d) prediction
- FFI initializes the model using the observations. Forecasts drift towards the climatology of the model.
- AI assimilates the observational anomalies in the hope of initializing the model closer to its own attractor in order to avoid drift / initialization shock
- Performance of both schemes have been studied using GCMs, with mixed results so far
- Need for a strategy to select the appropriate methods for the desired prediction

## 2. Objectives

1) Compare FFI and AI for a range of different observational and model error scenarios using an idealized coupled model
2) Introduce two advanced formulations: Least-Square Initialization (LSI) and Exploring the Parameter Uncertainty (EPU)
3) Selecting strategy for the initialization method

## 3. DA formulation of FFI and AI

- **FFI:** Model state is replaced by best available estimate of the actual state

$$x^a = x^b + H^T\left[y^o - H x^b\right] \qquad (1) \qquad H\text{: Observation operator}$$

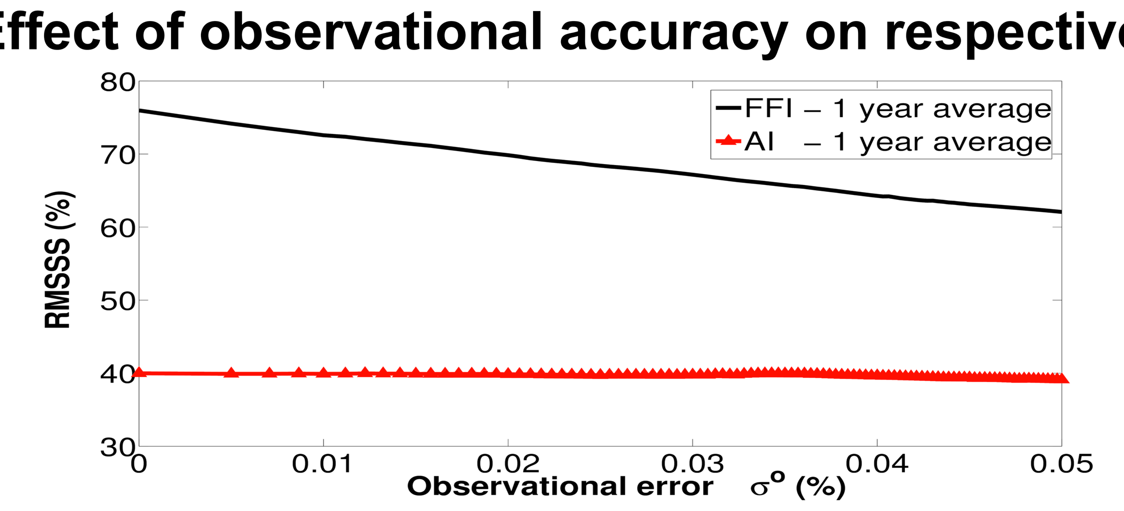
- **AI:** Observational anomalies are assimilated onto the model climatology

$$x^a = x^b + H^T\left[y^{pso} - H x^b\right]; \qquad y^{pso} = y^o - \left(\bar{y}^o - H\bar{x}^b\right) \qquad (2)$$

$x^b$: Background state obtained from a long control run of the model

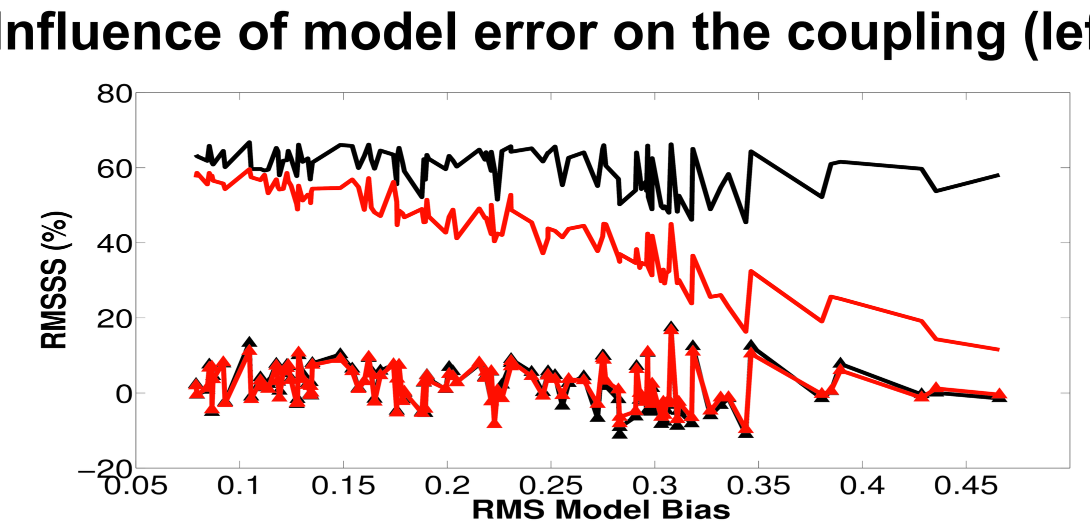
## 4. Comparison of AI and FFI

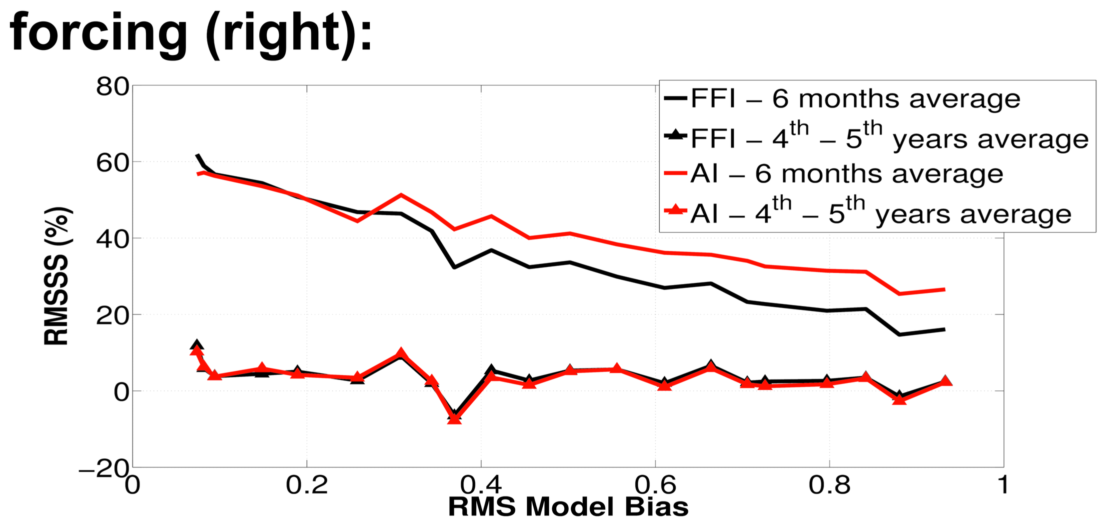
**Effect of observational accuracy on respective skill:**




In agreement with the error scaling properties from Eq. (1-2), FFI skill enhances after observational network refinements. In contrast, AI is far less sensitive to the observational error.

**Influence of model error on the coupling (left) and forcing (right):**



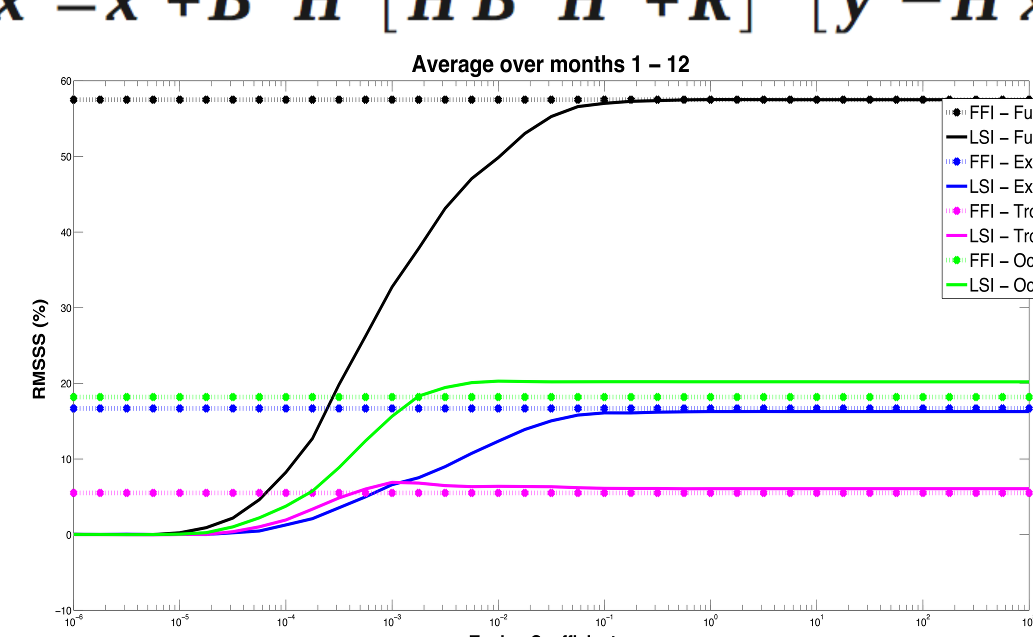

We observe two scenarios with regard to model error: One in which AI performs poorly compared to FFI for increasing model bias (left), and another in which AI outperforms FFI after a given model bias threshold (right). The latter configurations are furthermore associated with a rapid initial drift.

## 5. Advanced formulations

**•Least-Square Initialization:** $x^a = x^b + B^m H^T\left[H B^m H^T + R\right]^{-1}\left[y^o - H x^b\right]$

$$B^m = \alpha\,\overline{(x-\bar{x})(x-\bar{x})^T}$$

**Goal:** Propagation of observational information from data-rich to data-sparse regions of the model, based on an estimation of the error covariance using the statistics of the model anomalies

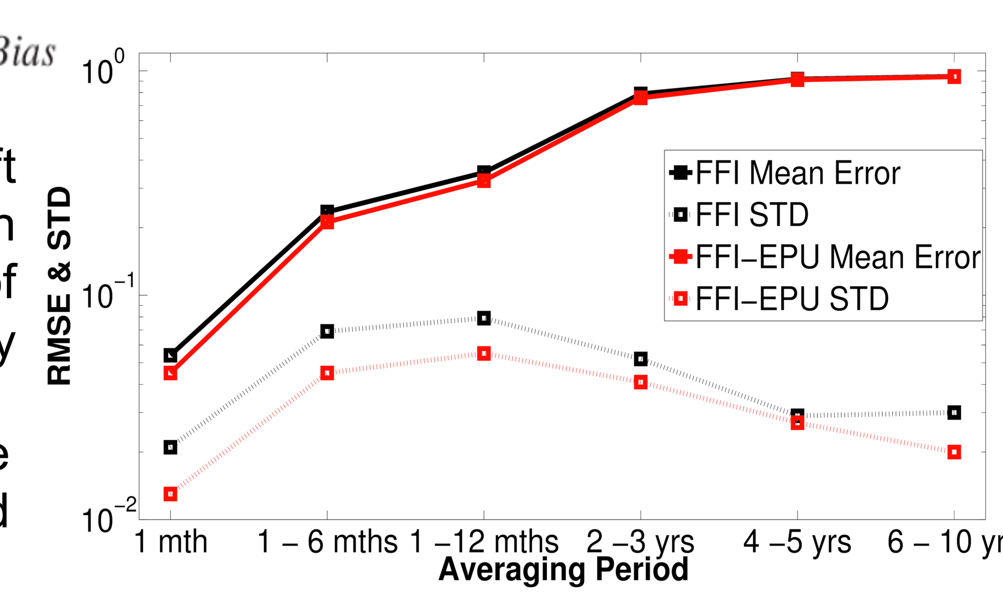



**•Exploring Parameter Uncertainty:** $x^{un}(t_i) = x(t_i) - b(t_i)$

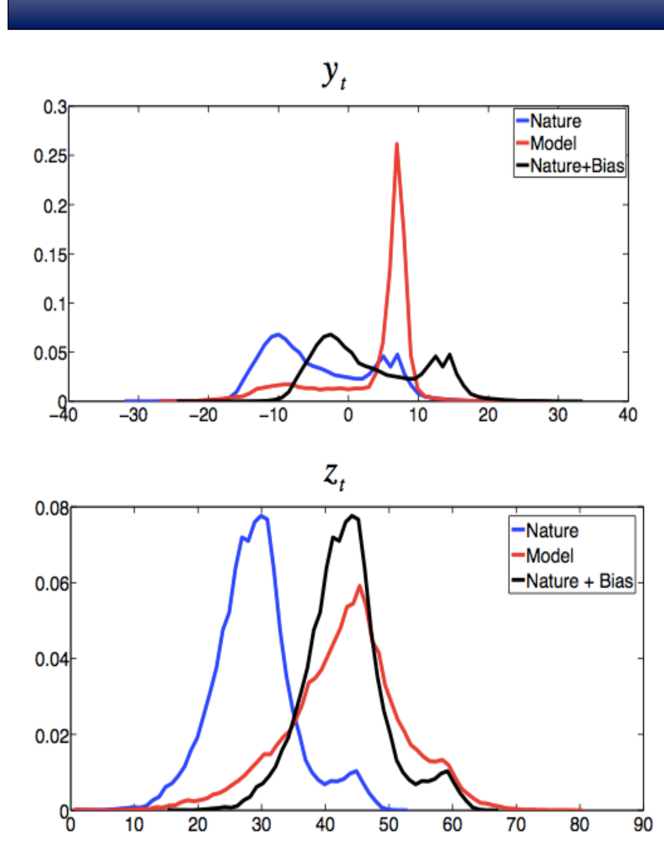
$$x^{un}(t_i) = x(t_i) - \left.\frac{\partial F}{\partial \lambda}\right|_{x(t_{i-1}),\lambda} \delta\lambda_i \Delta T_{Bias}$$

**Goal:** Correction of the drift during the forecast run based on a linear, short time estimation of the bias evolution originating only from parametric error

**Working hypothesis:** Choose uncertain parameters and sample from uncertainty range




## 6. Selecting the Initialization Method: FFI or AI ?



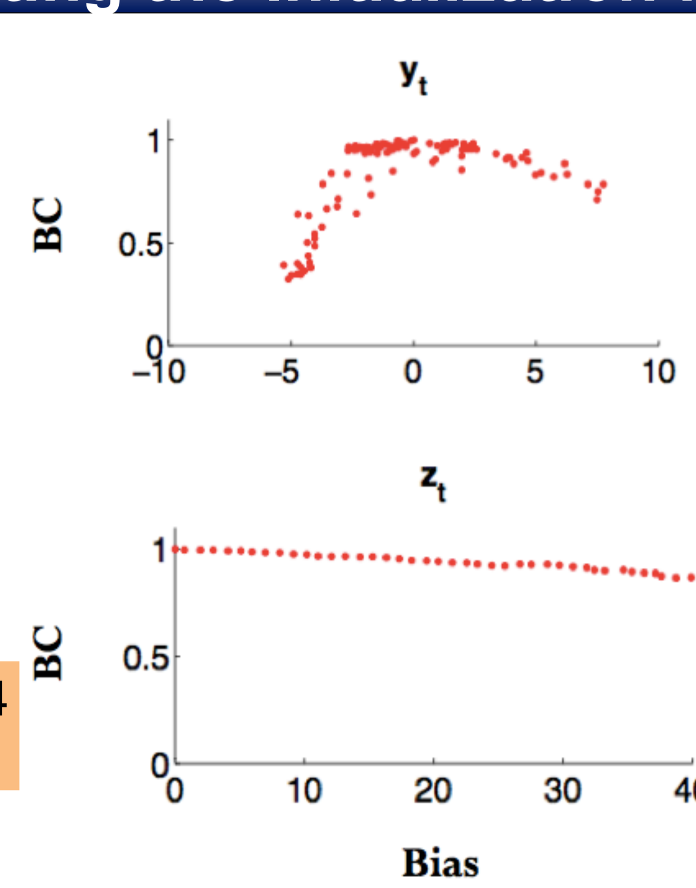

AI ✗ FFI ✓

AI ✓ FFI ✗

We can measure the similarity between the model PDFs p(x) and the initial conditions distributions q(x) using the Bhattacharyya coefficient:

$$BC(p,q) = \sum_{x\in X}\sqrt{p(x)q(x)}$$

Pena & Kalnay, 2004 model based on L63




➡ AI ✗

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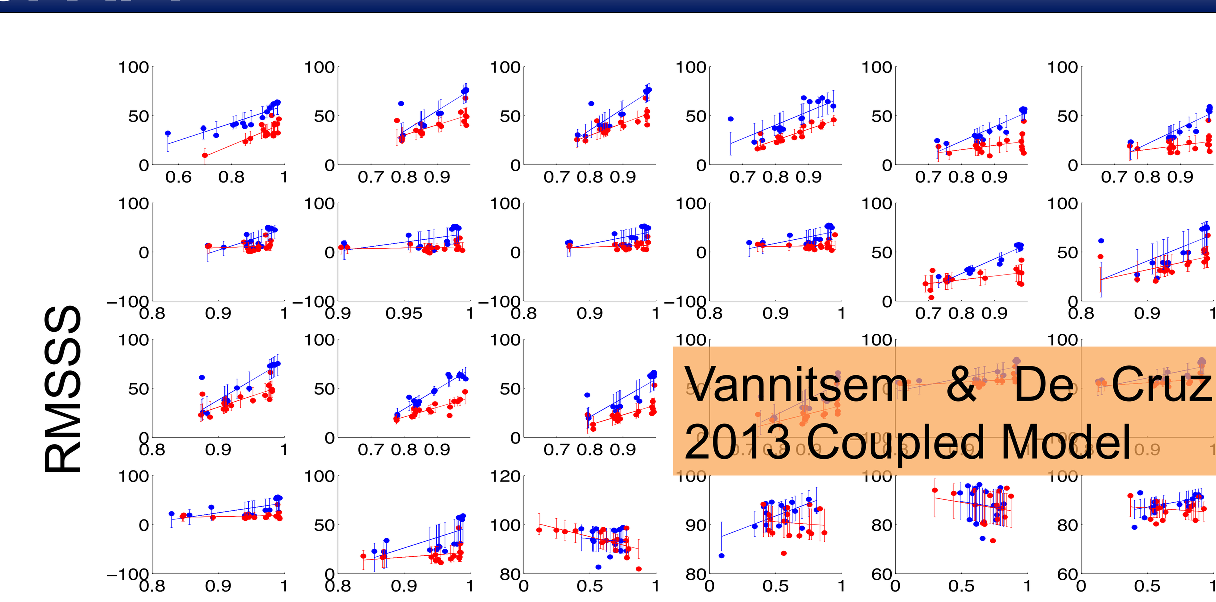


Vannitsem & De Cruz, 2013 Coupled Model

RMSSS as a function of BC for FFI (blue) and AI (red) in each of the model variable. The skill generally improves with BC.

## 7. Conclusions

- Improvements of the observational network influence the forecast skill of FFI more favorably than that of AI
- Relative performance of AI and FFI depends on the implemented model. In accordance with the assumptions of a linear correction scheme, AI is likely to perform better in cases in which the differences between the model and nature PDFs are limited to the first order moment. In these cases the skill (RMSSS) grows with the BC.
- LSI improves the performance of FFI in all situations in which only a portion of the system's state is observed due to an efficient propagation of information from data-rich to data-sparse areas
- EPU improves the skill of FFI within the first forecast year, with minor improvements for longer horizons

## 8. Key references

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3. Vannitsem, S. and De Cruz, 2013, A 24-variable low-order coupled ocean–atmosphere model, *Geosci. Model Dev. Discuss.*, **6**, 6569–6604, doi:10.5194/gmdd-6-6569-2013

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